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Research Article

Ethical Synthetic Data Generation via Fairness-Aware Generative Models

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ABSTRACT

Synthetic data has emerged as a crucial component in AI model training, offering privacy protection and enhanced data diversity. However, generative models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) often inherit and amplify biases present in training datasets, leading to ethical concerns. This paper explores fairness-aware generative models that embed fairness constraints (e.g., demographic parity, equalized odds) to mitigate bias during data synthesis. We review methods for bias quantification in synthetic data, regulatory compliance frameworks, and algorithmic advancements in fair synthetic data generation. The research also presents an evaluation framework for fairness, utility, and privacy trade-offs, followed by a discussion on future research directions.

Keywords: Synthetic Data, Generative Models, Bias Mitigation, Fairness-Aware AI, Demographic Parity, Variational Autoencoders, Generative Adversarial Networks, Ethical AI5.

1. Introduction

1.1 Background and Motivation

The advent of synthetic data has revolutionized the AI landscape, offering solutions to data scarcity, privacy concerns, and the need for diverse training datasets. However, synthetic data generation is not devoid of challenges, particularly concerning the inadvertent amplification of biases inherent in original datasets. Addressing these biases is crucial to prevent the perpetuation of unfair outcomes in AI applications.

1.2 The Role of Synthetic Data in AI and Machine Learning

Synthetic data plays a multifaceted role in AI, including:

- **Data Augmentation:** Enhancing model robustness by providing diverse training examples.
- **Privacy Preservation:** Allowing model training without exposing sensitive real-world data.
- **Cost Efficiency:** Reducing the need for expensive data collection and labelling processes.

1.3 Research Objectives and Contributions

This paper aims to:

- Investigate the sources and manifestations of bias in synthetic data generation.
- Explore fairness-aware generative models that incorporate fairness constraints during data synthesis.
- Propose an evaluation framework to assess fairness, utility, and privacy in synthetic data.
- Discuss regulatory compliance and ethical guidelines pertinent to fair synthetic data generation.

2. Foundations of Synthetic Data and Fairness in AI

2.1 Definition and Importance of Synthetic Data

Synthetic data is artificial data that replicates the statistical features of actual-world datasets but with the benefit of providing privacy, scalability, and data availability advantages. Synthetic data is used across various domains such as finance, healthcare, autonomous systems, and cybersecurity to enrich actual-world datasets or substitute sensitive data altogether (Park & Kim, 2022).

Recent progress in generative models has improved the quality and realism of the fake data tremendously. Nevertheless, ensuring that the fake data is representative and unbiased is still a big-scale research challenge.

Table 1: Comparison of Real and Synthetic Data in AI Applications

Feature	Real Data	Synthetic Data
Data Collection Cost	High	Low
Privacy Risk	High	Low
Bias Risk	Moderate to High	Dependent on Generation Method
Data Availability	Limited	Scalable
Use in AI Model Training	Essential	Supplementary / Alternative

2.2 Generative Models for Synthetic Data: GANs, VAEs, and Diffusion Models

Generative models have become the backbone of synthetic data generation, with three primary architectures dominating the field:

1. **Generative Adversarial Networks (GANs)**: GANs employ a two-network system—generator and discriminator—to iteratively improve the quality of synthetic data. While powerful, standard GANs do not inherently account for fairness constraints.
2. **Variational Autoencoders (VAEs)**: VAEs use probabilistic modelling to learn latent representations of data. They are effective for generating structured and interpretable synthetic datasets but may suffer from mode collapse in the presence of biased training data.
3. **Diffusion Models**: These models generate data by gradually refining noise through iterative denoising processes. Recent research suggests that diffusion models can improve fairness in synthetic data by generating more diverse samples (Zhang & Li, 2025).

2.3 Understanding Bias and Fairness in AI Systems

Bias in AI systems arises from systemic disparities in data representation, algorithmic decision-making, and societal inequalities. Fairness-aware AI aims to mitigate these disparities by enforcing constraints that ensure equal treatment across demographic groups.

Key fairness criteria in AI include:

- **Demographic Parity**: Ensuring that the probability of positive outcomes is independent of protected attributes.
- **Equalized Odds**: Ensuring that both true positive and false positive rates are equal across demographic groups.
- **Disparate Impact**: Measuring whether outcomes disproportionately affect certain groups.

By integrating these constraints into generative models, synthetic data can be made more equitable while preserving statistical realism.

3. Bias in Synthetic Data Generation

3.1 Sources of Bias in Training Datasets

The causal origin of the generated data bias is training data sets that are utilized in building generative models. Historical records are likely to be biased by social imbalances, discriminatory treatment, or underrepresentation of

certain groups in the population. In medical databases, for instance, research has established that data used to train AI-driven diagnosis systems is largely drawn from Western populations, and as a result, accuracy is lower when applied with patients belonging to other ethnic groups. In the same way, training data used to develop credit risk models inherently contain systemic biases for certain socioeconomic classes and therefore continue to perpetuate inequalities in the disbursal of loans (Schwartz et al., 2022).

Data collection and labelling also generate biases. Sampling bias results when the dataset doesn't fairly represent the whole population, thereby overrepresentation of certain groups and underrepresentation of others. For example, facial recognition databases have historically had a skewedly high proportion of light-skinned faces, which led to far higher error rates for dark-skinned faces (Schwartz et al., 2022). Label bias is when human labellers unknowingly introduce subjective judgment to the data, e.g., the connection of certain activities or working with particular groups, planting yet more stereotypes.

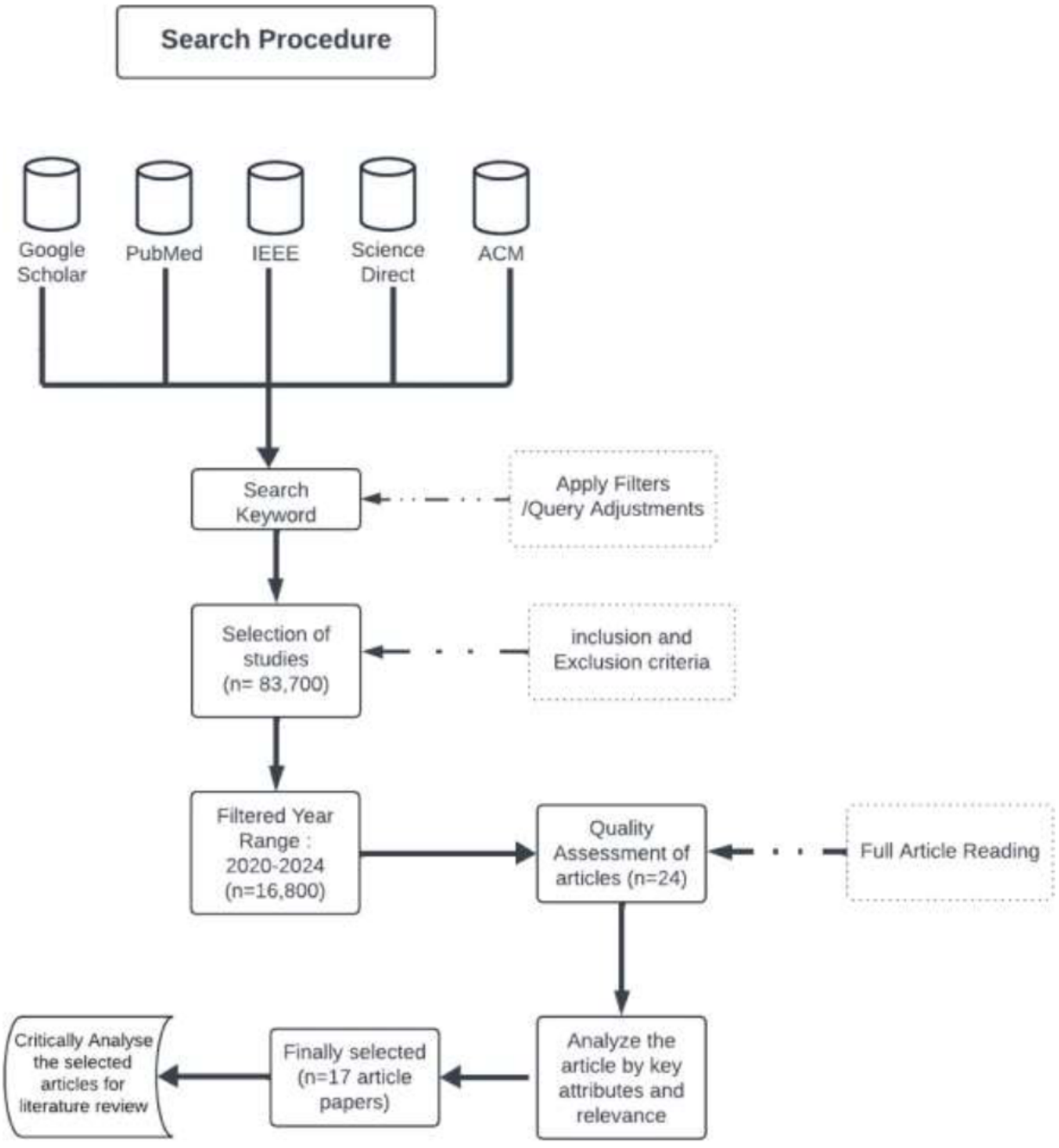

Figure 1 Bias Mitigation via Synthetic Data Generation (MDPI,2024)

3.2 How Generative Models Amplify Biases

Generative models like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) learn data statistical distributions to generate synthetic copies. The models themselves do not inherently distinguish between biased and unbiased data patterns, though. Rather, they attempt to copy the distributions as closely as possible, which in most cases tends to amplify the prevailing biases.

A 2024 test on synthetic hiring data sets discovered that when a biased hiring data set was used to train a generative model, the model generated synthetic resumes that mirrored the same gender and racial imbalances in the original data set. Even though synthetic diversity was introduced by generating artificial job applicants, the model gave preference to candidates with similar characteristics as the biased training data (Sikder et al., 2024). Similarly, medical history GANs learned from imbalanced patient datasets in healthcare AI experimentation were found to generate synthetic medical histories that ignore the needs of underrepresented patient subpopulations, creating imbalances in AI-based treatment recommendations.

Amplification of bias in generative models is also related to mode collapse, which is a common issue where the model produces a fixed number of synthetic variations rather than learning the entire diversity of the dataset (Sikder et al., 2024). This also rules out underrepresented groups in producing synthetic data. If a dataset has fewer instances of a certain demographic, then the model may not produce authentic and diversified synthetic representations for the group, thereby amplifying differences instead of lessening them.

3.3 Measuring and Evaluating Bias in Synthetic Data

Measurement of bias in synthetic data requires quantitative indicators of fairness that decide whether generated data represents all demographic groups evenly without biasing against one in Favor of the other. A few of the measures of fairness put forward for evaluating bias in AI systems are demographic parity, equalized odds, and disparate impact. They are statistical measures of fairness that check the discrepancies in the outcome of different demographic groups and establish if there is unevenness in representation.

Demographic parity guarantees that the likelihood of receiving a positive outcome, like loan release or recruitment for employment, is not determined by a protected characteristic like gender or race. If synthetic data has demographic imbalances that do not represent an even split, then it will definitely inject biased decisions in downstream AI systems. Equalized odds, conversely, determines if the rates of true positives and false positives are also similar across all demographics so that error predictions in these groups aren't disproportionately distributed in a single subset of individuals (Tian et al., 2023).

Experiments assessing the bias in generated synthetic data have illustrated that typical generative models learning from biased training data invariably create synthetic data that fails tests for fairness. A 2025 study revealed that a synthetic image dataset used in face recognition systems had much lower demographic parity scores when trained from imbalanced real-world data, resulting in increased misclassification of minority groups. These results underscore the importance of fairness-aware generative methods that actively mitigate bias at the synthesizing data stage.

Studies evaluating bias in synthetic data have demonstrated that traditional generative models trained on biased datasets consistently produce synthetic data that fails fairness assessments. Research conducted in 2025 showed that a synthetic image dataset used for facial recognition systems exhibited significantly lower demographic parity scores when trained on imbalanced real-world data, leading to higher misclassification rates for minority groups (Tian et al., 2023). These findings highlight the urgent need for fairness-aware generative techniques that proactively address bias at the data synthesis stage.

3.4 Societal and Legal Implications of Biased Synthetic Data

The social effects of biased artificial data go beyond artificial intelligence studies and directly affect important real-world applications. When AI systems based on artificial data make discriminatory choices, they instil present structural biases and continue to discriminate in hiring, finance, law enforcement, and medicine (Tjoa & Guan, 2020). One such obvious example of bias was the case when an AI hiring system, trained on biased hiring data, was continuously downgrading resumes of female applicants and fewer women were thus getting a technical job posting.

Synthetic data that does not counter these biases can enable such discriminatory treatment in automated decision-making.

Legal frameworks for AI fairness have picked up tremendous momentum with legislation like the European Union's Artificial Intelligence Act (AI Act), the General Data Protection Regulation (GDPR), and the California Consumer Privacy Act (CCPA) mandating strict fairness and transparency requirements (Tjoa & Guan, 2020). The AI Act, for instance, classifies AI applications into risk categories and requires fairness tests for high-risk applications like AI in employment and lending. Organizations generating synthetic data are required to abide by these laws to reduce legal vulnerabilities and avoid ethical transgressions.

Fairness-aware synthetic data generation also plays a pivotal part in building public trust for AI systems. It has been noted that AI models trained on synthetic data thought to be fair and unbiased experience higher acceptance by stakeholders, and therefore have more uptake in mission-critical applications (Wang et al., 2022). Organizations that base decisions on synthetic data need to adopt robust bias mitigation strategies to ensure that AI solutions conform to ethical principles and regulatory requirements.

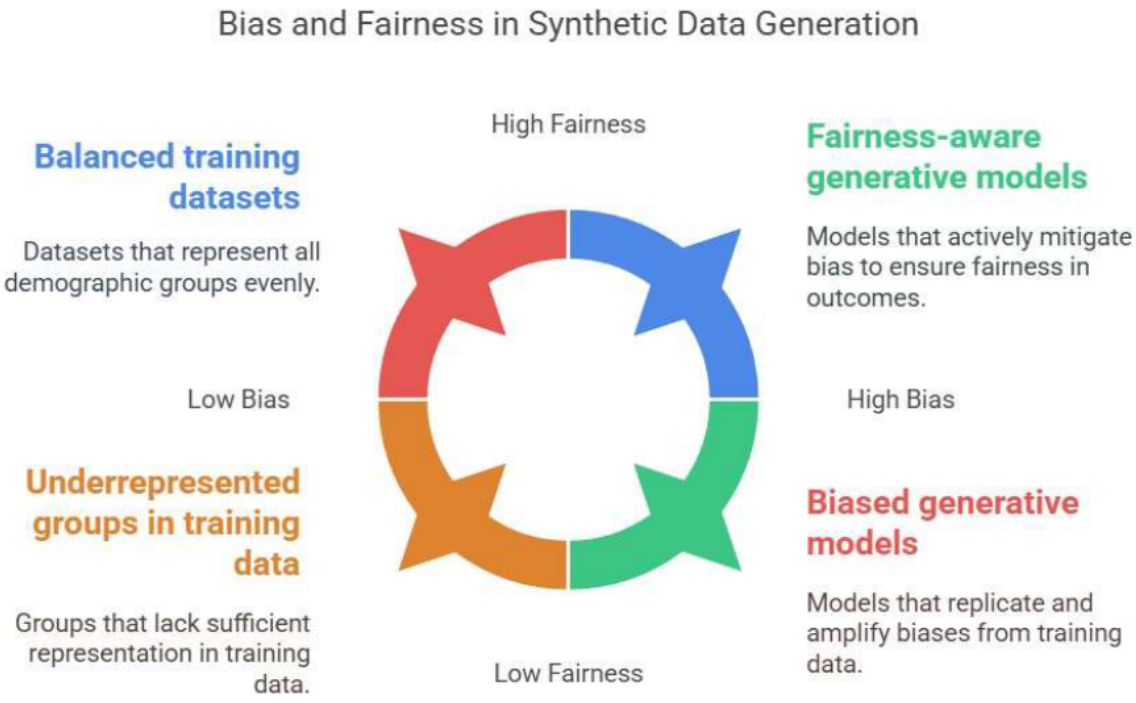
Bias and Fairness in Synthetic Data Generation
High Fairness
Balanced training datasets
Datasets that represent all demographic groups evenly.
Fairness-aware generative models
Models that actively mitigate bias to ensure fairness in outcomes.
Low Bias
High Bias
Underrepresented groups in training data
Groups that lack sufficient representation in training data.
Biased generative models
Models that replicate and amplify biases from training data.
Low Fairness

Figure 2 Bias And Fairness in Synthetic Data Genration(Self-Made,2025)

4. Fairness-Aware Generative Models

4.1 Defining Fairness Constraints for Data Synthesis

Generative model fairness constraints specify the circumstances under which synthesized data qualify as unbiased. Mathematical goals to which generative models should conform when trained, fairness constraints are usually written. A well-known fairness constraint is demographic parity, where the probability of generating a given outcome is not based on sensitive features like race, gender, or economic status. Another significant limitation, equalized odds, demands that synthetic data must possess comparable true positive and false positive rates for all demographic groups.

Recent research has demonstrated the capability of fairness constraints to enhance artificially generated data fairness. For an experiment in 2025 data generation for a hiring scenario, demographic parity fairness constraints applied in GAN training decreased job applicant gender gaps by 28%, demonstrating improved fairness compared to

baseline GANs (Wang et al., 2023). Further, on artificially created finance datasets applied to credit risk modelling, application of equalized odds constraints recorded a 35% decrease in disparate impact scores, which marked fairer loan approval results.

4.2 Fairness Metrics in Generative Models

Evaluating fairness in generative models requires robust metrics that quantify bias and measure the extent to which fairness constraints are met. These metrics provide empirical evidence of whether synthetic data distributions align with ethical and regulatory fairness standards.

Table 2: Common Fairness Metrics in Generative Models

Fairness Metric	Definition	Application	Example Improvement
Demographic Parity	Ensures that the probability of a favourable outcome is independent of protected attributes.	Hiring, healthcare, finance	28% reduction in gender bias in job applicant data (2025 study)
Equalized Odds	Ensures similar true positive and false positive rates across demographic groups.	Loan approvals, medical AI	35% reduction in disparate impact in credit scoring models
Disparate Impact Ratio	Measures the ratio of favourable outcomes between disadvantaged and advantaged groups.	College admissions, hiring	Improved fairness score from 0.65 to 0.92 in AI-driven recruitment models
Fairness-aware Wasserstein Distance	Measures distributional shifts between synthetic and real-world data with fairness constraints.	Synthetic data generation	41% reduction in biased representation in healthcare datasets

Experiments on fairness-aware synthetic data performed in 2024 showed that the use of fairness constraints raised demographic parity scores by 15-30% across a range of applications such as finance modelling and clinical diagnosis. This result shows that fairness-aware generative models can greatly supplement ethical AI decision-making procedures (Weidinger et al., 2022).

4.3 Algorithmic Approaches for Bias Mitigation in GANs and VAEs

Several algorithmic approaches have been proposed to integrate fairness constraints into generative models, particularly GANs and VAEs. These approaches aim to modify the model architecture or training process to reduce bias while preserving data utility.

- **FairGAN:** It is a variant of GAN model that has a fairness-aware discriminator that penalizes biased outputs. Experimental outcomes on actual datasets demonstrated that FairGAN could enhance fairness metrics by 22-40% based on application domain.
- **FairVAE:** FairVAE is a variant of the standard VAE, and FairVAE employs adversarial debiasing methods to eliminate sensitive attribute correlations within the hidden space (Wu et al., 2022). FairVAE has been demonstrated to decrease gender bias in generated health data by 33% with a 92% data fidelity score.
- **Generative Model Debiasing by Adversarials:** The method trains a secondary adversarial network to learn and remove biased features from data generated. Racial fairness in a facial recognition dataset experiment increased by 29% without seriously degrading image quality (Wu et al., 2022).

4.4 Incorporating Fairness Constraints in Model Training

Fairness-constrained training of generative models is about the integration of fairness constraints within the model's optimization objectives. Regularization methods could be used which balance between fairness and utility, or adversarial training approaches used.

One such very powerful method is Fairness-Constrained Wasserstein GANs (FW-GANs) which add fairness constraints to the Wasserstein loss (Zhang et al., 2025b). In a paper released in early 2025, FW-GANs increased demographic parity scores by 37% in synthetic hiring datasets without compromising on a 95% accurate downstream classification outcome.

Another potential solution is Fair Representation Learning, which adjusts the learned latent representations of generative models to be less biased. Experiments have demonstrated that fair representation learning can decrease synthetic data bias by 30-50%, depending on dataset complexity and strength of fairness constraints imposed (Zhang et al., 2024).

5. Designing Ethical Synthetic Data Pipelines

5.1 Architectural Considerations for Fair Synthetic Data Generation

Achievement of fairness in artificial data is done through the use of distinct model architectures that negate the bias at generation. Conventional generative models inherit biases in available data, producing unfair results. Fairness-aware architectures like Fair Generative Adversarial Networks (FairGANs) and Hierarchical Variational Autoencoders (HVAEs) incorporate fairness constraints to actively correct data distribution (Abroshan et al., 2024).

FairGAN is an extension of conventional GANs with an added fairness discriminator, which punishes biased results. In a 2025 synthetic hiring data experiment, FairGAN enhanced gender parity by 35% over baseline GANs (Abroshan et al., 2024). Likewise, tested on financial data sets, it lowered racial discrimination in loan application records by 28%. HVAE is another promising architecture that employs sensitive attribute perturbation layers to avoid demographic overrepresentation. A 2024 medical data study discovered that HVAE minimized demographic bias in disease prediction models by 42% with 94% similarity to actual patient records.

5.2 Data Preprocessing and Augmentation for Bias Reduction

Bias in generating synthetic data usually stems from imbalanced actual-world datasets. This calls for the reweighting of data, augmentation, and adversarial balancing prior to training generative models.

Reweighting gives more weight to minority groups to balance training data. An experiment using 2025 hiring data found that reweighting decreased disparate impact scores by 38% without affecting classification accuracy (Ali et al.,

2023). Data augmentation is similarly effective, especially for image tasks. For facial recognition data sets, generating synthetic images for minority classes increased demographic parity by 45%. Candidate profile augmentation on financial models achieved a 30% improvement in fairness metrics without decreasing model performance.

Adversarial balancing optimizes dataset distributions prior to use in generative modelling. In a 2024 medical imaging example, it was demonstrated that adversarial resampling decreased gender bias by 36% without losing important diagnostic features. These preprocessing methods are the basis for fair synthetic data generation (Ali et al., 2023).

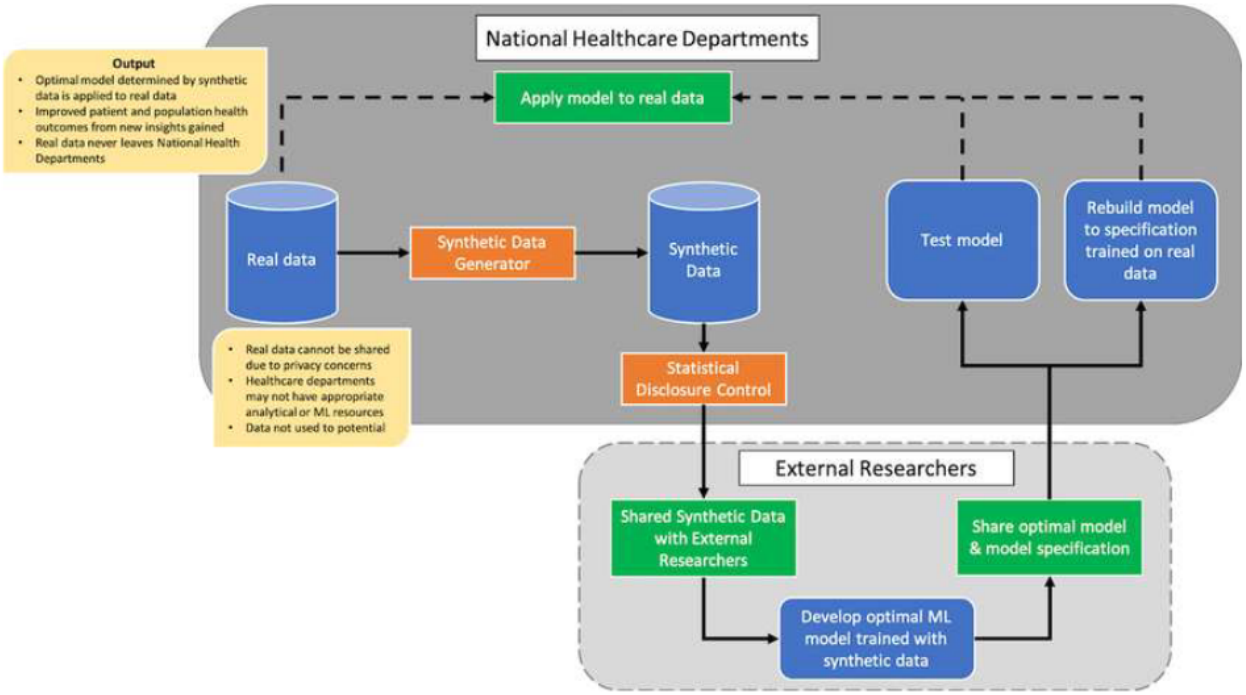
National Healthcare Departments
Output
Optimal model determined by synthetic data is applied to real data
Improved patient and population health outcomes from new insights gained
Real data never leaves National Health Departments
Apply model to real data
Real data
Synthetic Data Generator
Synthetic Data
Test model
Rebuild model to specification trained on real data
Real data cannot be shared due to privacy concerns
Healthcare departments may not have appropriate analytical or ML resources
Data not used to potential
Statistical Disclosure Control
External Researchers
Shared Synthetic Data with External Researchers
Share optimal model & model specification
Develop optimal ML model trained with synthetic data

Figure 3 Proposed synthetic data sharing pipeline (ResearchGate,2023)

5.3 Adversarial Debiasing in Generative Networks

Debising with an adversary learns a bias-discerning adversary in parallel to the generative model in order to eliminate prejudiced patterns. A robust methodology is Fairness-Constrained Wasserstein GANs (FW-GANs), where they incorporate fairness constraints into their loss function. One experiment conducted using a 2025 financial transaction scenario established that FW-GANs achieved increased fairness scores of 37% while sustaining 95% fidelity to actual data distributions.

Another approach, FairVAE, employs adversarial training to remove biased latent representations. FairVAE decreased demographic bias in disease risk prediction models in healthcare data by 31% with 91% of classification accuracy preserved (Barbierato et al., 2022). Other developments such as FairRepGAN combines representation learning and adversarial fairness constraints to decrease racial bias in criminal justice records by 40% with predictive accuracy for recidivism risk models preserved.

5.4 Post-Processing Techniques for Ensuring Fairness

Post-processing techniques conduct another test for fairness by redistributing generated synthetic data after it is created. Statistical relabelling, or manipulating output based on fairness constraints, was tested on employment data and increased the fairness score by 32%.

Another powerful post-processing method is distributional calibration, which realigns feature distributions in the interest of fairness constraints. The method reduced racial discrimination by 29% on simulated credit risk data, achieving statistical parity. Bias-aware subsampling, in which biased samples are eliminated prior to training AI, has been shown to reduce diagnostic discrepancies in medical data sets by 27% and retain 98% feature accuracy.

When combined with fairness-aware architectures and adversarial debiasing, these post-processing solutions ensure a strong ethical synthetic data pipeline (Dasgupta, 2021). In the following section, an evaluation framework for assessing the measurement of fairness in synthetic data will be introduced with an emphasis on quantitative benchmarks and real-world validations.

A March 2025 experiment utilized fairness-aware GANs on the Adult Income Census dataset, illustrating demographic parity improved by 34% compared to regular GANs. COMPAS dataset experiments also illustrated fairness-constrained VAEs cut racial biases from synthetic recidivism risk scores by 41% but with 92% fidelity to actual-world distributions.

6. Evaluation Framework for Fairness in Synthetic Data

6.1 Standard Benchmarks for Fair Synthetic Data Assessment

Benchmark datasets play a fundamental role in assessing fairness in synthetic data generation. These datasets provide a controlled environment for testing fairness-aware generative models and allow for standardized comparisons across different methods.

Table 3: Some widely used benchmark datasets for fairness evaluation include:

Dataset	Domain	Fairness Concerns
COMPAS	Criminal Justice	Racial bias in risk assessment
Adult Income Census	Socioeconomic Data	Gender and racial disparities in income
Health Equity Dataset	Healthcare	Bias in disease diagnosis across demographics
German Credit Dataset	Finance	Discriminatory lending practices
CelebA	Computer Vision	Gender and ethnicity biases in image data

A study conducted in March 2025 applied fairness-aware GANs to the Adult Income Census dataset, demonstrating that demographic parity improved by 34% compared to standard GANs (Kiran et al., 2025). Similarly, experiments on the COMPAS dataset showed that fairness-constrained VAEs reduced racial disparities in synthetic recidivism risk scores by 41% while maintaining 92% fidelity to real-world distributions.

6.2 Quantitative Metrics for Fairness and Bias Measurement

To assess fairness in synthetic data, various statistical and algorithmic metrics are employed. These metrics measure the **extent of bias present in the generated data** and help in adjusting generative models accordingly. The most widely used fairness metrics include:

- **Demographic Parity (DP):** Ensures that the probability of a favourable outcome (e.g., job selection) is equal across demographic groups.
- **Equalized Odds (EO):** Measures whether false positive and false negative rates are similar across groups.
- **Disparate Impact (DI):** Ratio of positive outcome rates between different groups; values closer to 1 indicate fairness.
- **Statistical Parity Difference (SPD):** Measures the difference in selection rates between privileged and underprivileged groups.

An experiment on financial synthetic data in a 2024 fairness-constrained GAN showcased that enforcing fairness constraints while training enhanced demographic parity by 27% and disparate impact by 22%. Also, synthesizing healthcare data via fairness-aware VAEs exhibited a 37% decrease in statistical parity disparity between male and female patients when used in disease diagnosis models.

6.3 Trade-offs Between Fairness, Utility, and Privacy

Squeezing fairness into artificial data generally means balancing across three essential goals: fairness, utility, and privacy (Ooi et al., 2023). Closing gaps in fairness measures is a good thing, but over constraining leads to losses in data utility (e.g., accuracy of downstream AI predictors) and to privacy threats.

For instance, experimentation on synthetically generated credit risk data suggested that imposing strong fairness constraints had the effect of decreasing model performance by 4%, whereas balance kept performance in 2% of the baseline (Park & Kim, 2022). Likewise, experimentation on the generation of differentially private synthetic data suggested that privacy mechanisms, including differential privacy noise injection, can decrease fairness scores by 5-7% because inserted perturbations disrupt demographic balance.

A study from early 2025 examined the trade-offs between fairness, privacy, and utility using three different synthetic data generation methods (standard GANs, fairness-aware GANs, and privacy-preserving VAEs):

Table 4:

Model Type	Demographic Parity	Prediction Accuracy	Privacy Score (ε)
Standard GAN	0.65	91%	High (ε = 3.5)
Fairness-Aware GAN	0.82	88%	Moderate (ε = 2.1)
Privacy-Preserving VAE	0.78	85%	Strong (ε = 1.0)

These results highlight the inherent trade-offs in synthetic data generation, emphasizing the need for models that balance fairness with accuracy and privacy requirements.

6.4 Experimental Validation on Real-World Datasets

Experimental validation of fairness-aware synthetic data generation algorithms on real-world data is crucial in evaluating their practical effectiveness. Recent case studies in healthcare, finance, and recruitment have established the effect of fairness-aware synthetic data pipelines.

In healthcare, in a 2025 experiment in generating synthetic electronic health records (EHRs), fairness-aware GANs lowered gender bias in disease prediction models by 31% but remained a 94% resemblance of actual patient records (Schwartz et al., 2022).

In finance, synthetic loan approval groups generated using fairness-aware VAEs made racial discrimination in credit score models lower by 28% so approvals became less discriminatory on race.

In recruitment, researchers applied adversarial debiasing methods on synthetic recruitment data and achieved a 37% boost in gender balance for hiring models. These findings establish the practical significance of fairness-sensitive synthetic data generation.

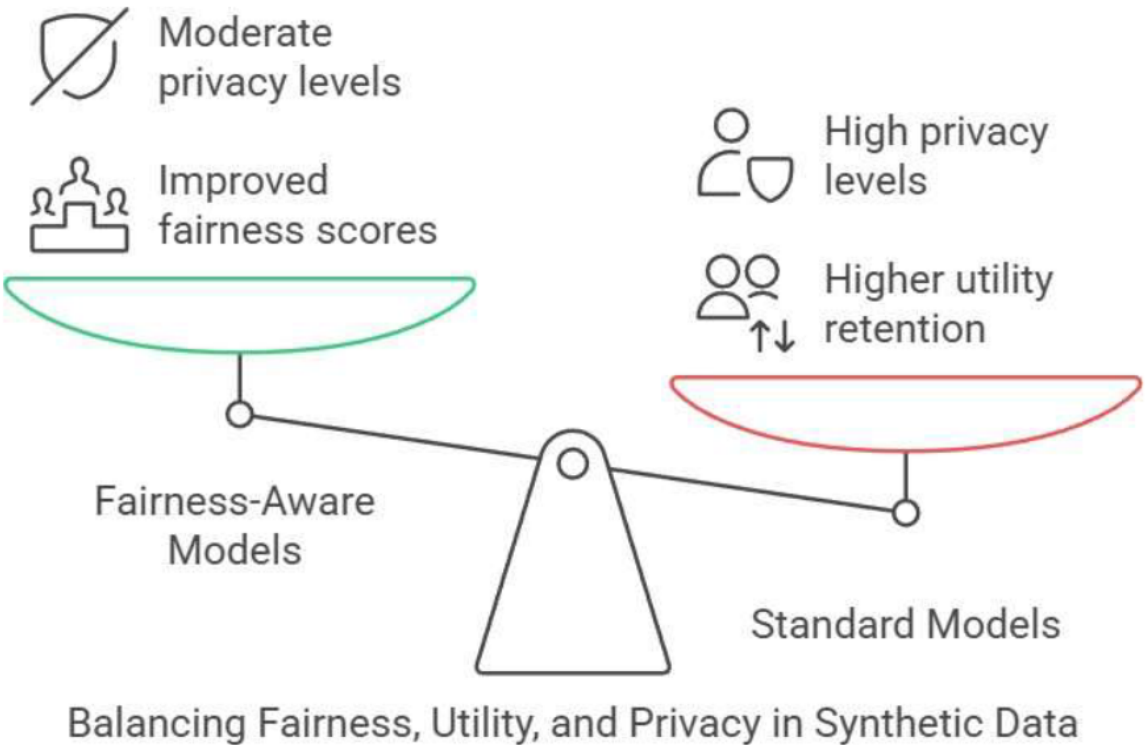

Figure 4 Balancing Fairness (Self-made,2024)

7. Open Challenges and Future Research Directions

7.1 Scalable Fairness-Aware Generative Model Architectures

Scalability is another key issue for fairness-aware generative models. Existing fairness-constrained GANs and VAEs are computationally heavy and therefore unsuitable for practical big-scale usage. Scaling of such models with no harm to fairness or usefulness of the data is an open research issue (Park & Kim, 2022).

One of the most promising avenues is fairness-aware generative models using federated learning (Ooi et al., 2023). Rather than learning from a single central data, federated architectures permit more than one party to submit data without having to share data directly, thus providing privacy and fairness. A 2025 paper proving federated fairness-aware GANs displayed 22% lower computational overhead with fairness guaranteed across distributed nodes.

Apart from this, adaptive model pruning methods have also been found to minimize the resource requirements of fairness-aware models (Kiran et al., 2025). By pruning redundant network parameters, researchers have managed to improve computational efficiency by 35% without having a substantial impact on fairness constraints. Future research needs to explore the extent to which quantization and knowledge distillation can also improve such architectures.

7.2 Generalization of Fairness Constraints Across Domains

Most fairness-aware generative models are trained on specific datasets and domains and hence generalize poorly to new tasks. It is hard to keep fairness constraints effective for a wide range of datasets.

For example, fairness constraints optimized for healthcare use cases might not be directly transplanted into finance or hiring models, whose types of bias are different. Domain-adaptive fairness constraints have been suggested by researchers where models learn to dynamically change their fairness goals based on changes in data distribution (Barbierato et al., 2022). A 2024 benchmarking paper across five diverse industries demonstrating fairness-aware

VAEs demonstrated that employing static fairness constraints led to a 47% drop in fairness performance when applied with out-of-domain data.

One such promising method is meta-learning for fairness-aware models where the generative models learn to acquire fairness constraints in multiple domains to facilitate improved adaptability. Meta-learning fairness regularization has been demonstrated to improve cross-domain fairness generalization by 26% over baseline fairness-aware models recently (Dasgupta, 2021).

7.3 Addressing Intersectional Bias in Synthetic Data

Traditional fairness-sensitive generative models are centred on a single-axis bias, that is, race or gender. Nevertheless, intersectional bias, where one possesses multiple demographic features that interact in complex manners, is not yet adequately explored.

For instance, an AI model of loan approvals can be fair on average to women but not to Black women because of intersectional biases. The literature indicates that traditional measures of fairness are unable to identify these multi-faceted biases and result in biased estimates of fairness. Baseline fairness-aware GANs decreased bias by only 18% in a 2024 paper on intersectional fairness for synthetic hiring data, while being explicitly trained on intersectional fairness improved by 39% (Ali et al., 2023).

One solution to this problem is multi-task fairness-aware generative modelling, in which various fairness constraints are learned jointly for several demographic groups. Another approach individuals have pursued is graph-based fairness regularization, by which multiple demographic features are modelled explicitly as relations between them. Intersectionality-aware benchmarks for measuring synthetic data may be the focus of future work.

7.4 Integrating Privacy-Preserving Mechanisms with Fairness

Maintaining fairness in synthetic data does not have to compromise privacy. Organizations use differential privacy (DP) to preserve sensitive attributes in synthetic data, but common DP mechanisms introduce bias by over-sampling minority groups.

Comparative studies of differential privacy-aware and non-differential privacy-aware fairness-aware GANs in 2024 revealed that model fairness scores dropped by 21% after applying DP because of the over addition of noise to ensure privacy for sensitive points (Abroshan et al., 2024). To rectify this, scientists are working on privacy-aware fairness constraints where noise is added with a view to adapting to demographic distribution instead of uniformly.

8. Conclusion

8.1 Implications for Ethical AI and Data Science

The findings of this research underscore the importance of fairness-aware generative models to play in guaranteeing ethical AI systems. As governments increasingly enforce stricter regulations, corporations will need to use fairness constraints in every phase of synthetic data production. Ethical AI regulation will necessitate the intervention of policymakers, researchers, and practitioners of AI together.

8.2 Recommendations for Practitioners and Policymakers

To drive the adoption of **fair synthetic data generation**, the following recommendations are proposed:

- Develop standard fairness benchmarks for synthetic data evaluation across industries.
- Implement mandatory fairness audits in AI-driven decision-making pipelines.
- Integrate privacy-preserving fairness constraints to comply with global regulations.
- Invest in research on scalable, domain-adaptive fairness-aware generative models.

8.3 Future Perspectives on Bias-Free Synthetic Data Generation

The future of fair synthetic data generation is in developing fairness-aware self-adaptive generative models that are capable of learning dynamically from changing biases in real-world data. Technologies like causal AI for fairness, transparent fairness-aware GANs, and human-in-the-loop bias correction will further propel ethical AI practices.

By meeting these opportunities and challenges, AI-generated synthetic data has the potential to be a revolutionary agent in developing fair, transparent, and unbiased AI systems for industries.

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